IoT, Big Data, and Artificial Intelligence in Agriculture and Food Industry

N. N. Misra, Yash Dixit, Ahmad Al-Mallahi, Manreet Singh Bhullar, Rohit Upadhyay, and Alex Martynenko

***Abstract*—Internet of Things (IoT) results in a massive amount of streaming data, often referred to as "big data," which brings new opportunities to monitor agricultural and food processes. Besides sensors, big data from social media is also becoming important for the food industry. In this review, we present an overview of IoT, big data, and artificial intelligence (AI), and their disruptive role in shaping the future of agri-food systems. Following an introduction to the fields of IoT, big data, and AI, we discuss the role of IoT and big data analysis in agriculture (including greenhouse monitoring, intelligent farm machines, and drone-based crop imaging), supply chain modernization, social media (for open innovation and sentiment analysis) in food industry, food quality assessment (using spectral methods and sensor fusion), and finally, food safety (using gene sequencing and blockchain-based digital traceability). A special emphasis is laid on the commercial status of applications and translational research outcomes.**

***Index Terms*—Blockchain, digital, gene sequencing, Internet, precision agriculture (PA), robotics, sensors, social media.**

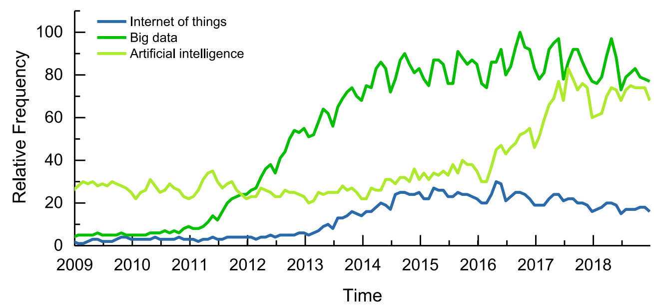

Fig. 1. Relative worldwide search traffic for the terms IoT, big data, and AI on Google over the last decade. Data accessed from Google Trends on June 16, 2019. Numbers represent search interest relative to the highest point on the chart for the given time. A score of zero means that there was not enough data for this term.

I. Introduction

Internet of Things (IoT), big data, and artificial intelligence (AI) are perhaps old buzzwords in the tech industry, that are making an impact only in very recent times. In fact, data from Google Trends search history for these topics shows that IoT and big data have drawn the considerable interest of broad-based Internet users within the last five to six years, while AI remains a topic of interest for much over a decade (see Fig. 1). In fact, with the increase in communication devices the volume of data generated is rising and AI is continuing to well integrate into the lives of a big population of the planet in one form or the other. Unlike AI, IoT primarily being industrial technology remains to be of low interest to the general public. A natural topic of interest for agri-food scientists and engineers would be to maximize the impacts of these emerging information technologies for sustainably feeding the planet. As a first aim of this review, we will begin by briefly introducing these topics for those audiences who are coming from a background in agriculture and food sciences.

First coined by Kevin Ashton, IoT is a technology paradigm contemplated as a vast network of digitally connected devices and machines [1]. Here, the digital connection of the machines or "things" occurs over "Internet." IoT is sometimes also referred to as the Internet of Everything or the Industrial Internet. The influence of IoT arises from its ability to enable robust communication between the physical world with that of the digital, a concept often referred to as the fourth industrial revolution. In fact, the use of IoT in industry is sometimes also referred to as Industrial IoT (IIoT). In the IIoT framework, remote sensors gather information generated by machines (and increasingly, humans too) to increase efficiency, promote better decision making, and build competitive advantages, regardless of industry or company size. IoT platforms serve as the bridge between the devices' sensors and the data networks, wherein the connected IoT devices exchange information using Internet transfer protocols. The sensors of the devices within an IoT network yield large volumes of data that continuously stream to a "data lake," which could be a local physical server or cloud-based storage (i.e., distributed across the Internet worldwide) for enabling necessary data processing via appropriate algorithms or machine learning (ML) techniques to generate actionable insights. Thus, we note that IoT is essentially the

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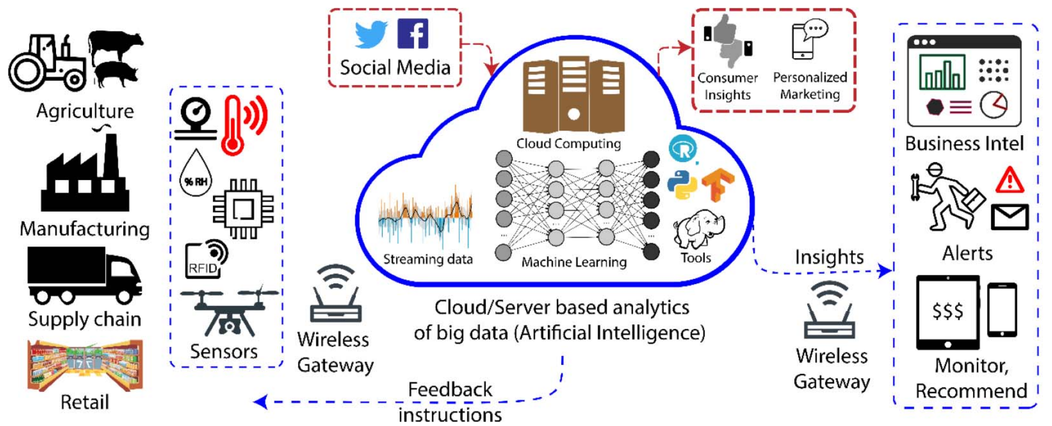

Fig. 2. Pictorial representation of the IoT framework within agri-food industry context.

means generating and transmitting large amounts of data with information of practical use embedded in it.

The concept and scope of big data, as a matter of fact, lacks a formal definition. Big data in the IoT context does not only refer to the structured or unstructured data but also includes the aspects of analytics, insights, and (automated) decisions, all of which typically happen in real time. In addition to the massive data generated from devices/sensors, the social media is an important source of user-generated big data, which deserves special discussion. Though increasingly valuable, one should note that the social media data does not (strictly) fall into the IoT framework. We will discuss the usefulness of social media big data analytics later in this review in a dedicated section. The recent developments in ML, AI, and boom in the data science field, coupled with improvements in computing power has enabled the automated decision support, real-time analytics for insights, and better performance of supervised (learning) models. A discussion of the relevant ML tools for AI is also included later in this review.

In Fig. 2, we provide a graphical summary of the IoT and big data framework in agri-food context to facilitate discussion of several concepts within our review. Here, we note that the data can come from agriculture, food processing/manufacturing, supply chain, traceability, or consumers. While sensors are points of data source in case of IoT, data from consumers comes in the form of opinions shared on social media platforms. The data from multiple sensors and sources when appropriately combined, it provides information about the primary production or processing or retail activities. Upon suitable analysis of the information using computer models, the information is transformed into knowledge about the performance of the said activities. In modern times, the data processing typically occurs at remote locations using high performance computers; this is known as "cloud computing." The knowledge obtained about the system can be leveraged to make decisions for improving the performance of the activities or make suitable recommendations. When this entire process from data to decision is automated through self-learning methods, it is known as AI. This trend of high level of automation in industry using cyber–physical systems, IoT, cloud, and cognitive computing put together is known as "Industry 4.0," literally meaning the fourth industrial revolution [2].

In this review, we take a holistic approach to several frontier areas dealing with agri-food-consumer triad, bridging the language barrier among the disciplines of agricultural, food, electronics, and computer science. The applications we have chosen for discussion are based on our experiences as well as those of high significance to the global agriculture and food industry. The discussions are based around the IoT devices—the sources of data, basic data processing, the disruption brought about by the technology, the implementation challenges, as well as research needs. We target this review at hardcore electronics, instrumentation and computer engineers, as well as, agri-food scientists, to provide an exposition of the meaningful impacts created by the new cyber–physical technologies. We hope that a cross-fertilization across the vast landscape of topics will motivate further research for building agri-food Industry 4.0.

II. From Data to Action

Sensing is the birthplace of all data in IoT. Agri-food sector produces a large number of diverse datasets, both in content, structure, and storage format with the use of various IoT devices [3]. Common characteristics of big data include heterogeneity, variety, unstructured nature, noise, and high redundancy [4]. Such huge amounts of data require complex methods for data curation and storage, as well as intensive statistical approaches and programming models to extract relevant information. The conditioning and preprocessing of primary data results in the information required to understand the state of the (agri-food) system. By applying advanced algorithms and measuring the performance of the system with respect to the desired outcome, a system can be made capable of making independent localized decisions and take appropriate actions. This level of independence allowing autonomy in sensing, decision making, and actuation is what makes an IoT system "intelligent."

The field of AI involves the development of theory and computer systems capable of performing tasks normally requiring human intelligence, such as sensorial perception and decision making. Kaplan and Haenlein [5] defined AI as "$\cdots$ *a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve*

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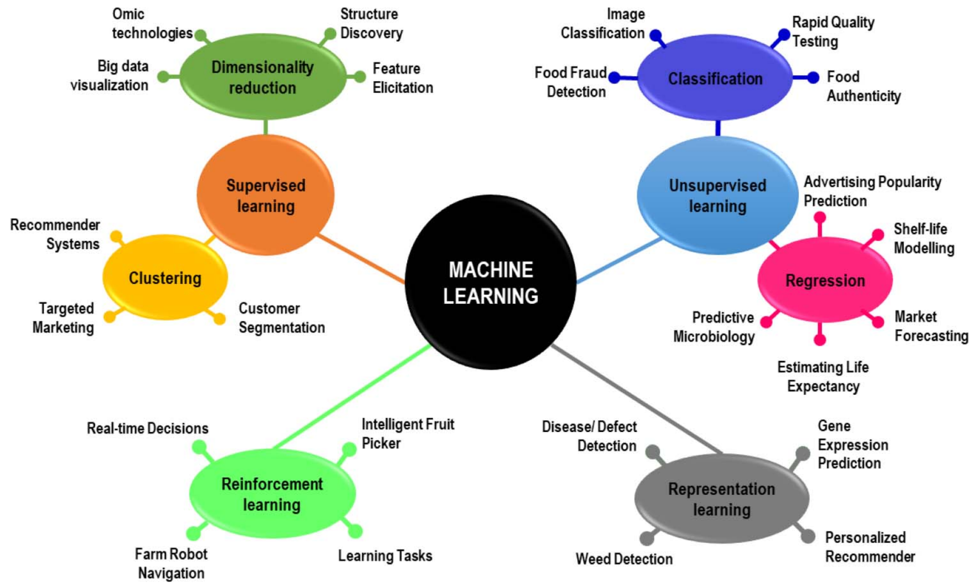

Fig. 3. ML paradigms and their applications in the agri-food space.

specific goals and tasks through flexible adaptation." Thus, AI acts on external information sourced from IoT and other big data sources, uses knowledge-based rules (provided by developers) or identifies the underlying rules and patterns using ML, to drive the systems toward set objectives. A truly intelligent system can learn, generalize (if there be such scope), accumulate knowledge, set objectives and priorities, and minimize risks for decision-making processes.

AI can be brought into industry through "expert systems" built on rules, and this approach is referred to as "rule-based" AI [6]. The collection of all rules governing the behavior of the system are either based on physical principles or experience-based human expert knowledge. In this approach, the system or process is constantly monitored using IoT devices or sensors. The IoT sensors yield data about individual system descriptors which are analyzed using the rules. The raw data are occasionally also curated and stored into a database to depict trends. It is to be noted that the complexity in agri-food systems is very high due to the involvement of many unpredictable variables in agriculture, the heterogeneity of food materials, and the food habits of consumers. This makes it almost impossible to translate the farmers, industry experts, and consumers knowledge into clearly expressed, well-defined rules (computer programs) that can be implemented into AI-based expert systems [7]. Nevertheless, rule-based AI is suitable in scenarios where real-time decisions and control are a necessity, and when one cannot afford to frequently train the AI system.

Considering the drawbacks of rule-based AI, ML-based AI has become more popular in recent times [8]. In ML-based AI, there may be a lag period between data collection (sensing) and making predictions or decisions, as the system is programmed to look for patterns in the data collected (e.g., from IoT sensors). Presently, ML-based AI systems do not involve the use of human intelligence-based computer rules (i.e., compliance with any kind of science or physical reality or expert experiences); rather, these are purely data driven. ML-based AI is suitable for systems where frequently training the system is not a constraint and higher accuracy is desired, which is quite true for agri-food systems.

ML is one of the central topics of AI, since a feature usually attached to intelligence is the ability to learn from the environment. ML is a technique for developing AI which gives computer the ability to learn without being explicitly programmed [9]. Simply put, ML algorithms distill and coalesce knowledge from unorganized data in a manner that their outputs are computer programs able to accomplish useful tasks, such as alert a user or actuate critical steps [7]. It explores the study and structure of algorithms that can learn from and make predictions on data; such algorithms overcome strictly static programing instructions by making data-driven predictions/decisions [10]. ML algorithms can be broadly classified into the following four main categories.

1) *Supervised Learning:* These algorithms receive labeled data as training sets and make predictions for unseen points.
2) *Unsupervised Learning:* These algorithms receive unlabeled data as training sets and make predictions for unseen points.
3) *Reinforcement Learning:* These algorithms continuously interacts with the environment, under certain cases it affects the environment, and receives award for each action; the objective here is to maximize the reward over a course of actions and iterations with the environment [11].
4) *Representation Learning:* It also known as *feature learning*, these include a set of methods that allow a machine to be fed with raw data and to automatically discover the representations needed for detection or classification [12]. The widely acclaimed deep learning based on neural networks is the best example of representation learning.

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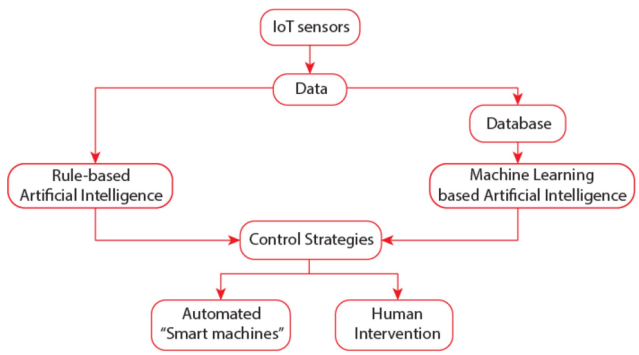

Fig. 4. Simplified workflow from data to action in the IoT ecosystem, and the role of AI.

Fig. 3 shows various models under these mentioned categories and their technological applications. Detailed discussions about ML methods and their agri-food specific applications can be found elsewhere [9], [13].

Owing to its unprecedented impacts, the area of deep learning with neural networks deserves a special mention. Deep learning methods enable the extraction of high levels of information from very large volumes of data. Unlike traditional ML methods, the algorithms in deep learning are hierarchically organized according to increasing complexity. The computational models in deep learning comprise of multiple processing layers to learn representations of data with multiple levels of abstraction [12].

The overall flow of data from source, through the data processing or AI platform, until the final action—usually some kind of control, is summarized in Fig. 4. AI techniques are advancing rapidly, but most upcoming applications will likely involve a combination of both rule-based analysis (to represent first principle constructs in the data) and new AI methods. This is especially the case when daisy-chaining data sets through a supply chain. Furthermore, data and new algorithms are expected to be combined with practiced human domain expertise, so that people will understand and trust the process by which computer programs came to their conclusions.

The end objective of AI or big data workflow is usually some kind of process control or automation in the industrial context. Nonetheless, the end application of all IoT, big data analytics, and AI systems is context dependent, and besides automation, cloud also involve obtaining insights, making predictions, and providing alerts (fault detection). The final nodes of the learning methods in Fig. 3 provide some common examples of end applications for which the insights from data are generated using the ML tools.

III. Big Data and IoT in Smart Farming

With the planet's population projected to reach almost 10 billion by 2050, innovative approaches to food production will be required to meet the food demands. However, the current rate of agricultural yield increases is way below than those predicted to be met for feeding the world in future [14]. Therefore, much like in the 1970s when we had the first agricultural revolution, the world needs to see a disruption in the agricultural practices. It is imperative that novel and smart solutions are developed for global food security, food safety, sustainable food-consumption, and health and well being of society. Technologies that could enable reduced use of resources for agriculture, e.g., water, fertilizers, and agrochemicals, and help to significantly cut down the carbon footprint of farming will be important drivers for global agricultural sustainability. Likewise, environment friendly intervention strategies that protect food crops or food products from decay or pests, which lead to reduced losses and/or allow extension of shelf life are important levers to address global food security challenges. The application of modernized technologies in agriculture is broadly referred to as "smart farming." Of the many developments, the use of 1) sensors deployed to monitoring farm conditions and 2) low altitude air-borne hyperspectral imaging are topics we consider worthwhile discussing in this review. A detailed review of the role of big data in smart farming is already available [15]; hence, our aim is to provide an exposition of the developments where many agri-food-automation companies are actively contributing or reaping the benefits.

A. Connected Field Sensors and Machines

Precision agriculture (PA) is a management concept that recognizes variability within the soil environment and maximizes economic agricultural production while minimizing the environmental impact for a specific location [16]. PA is all about applying the right material in the right amount at the right location and right time, which is known as the 4R concept [17], [18]. Since its introduction in the 1990s, PA has had high expectations to increase the efficiency of agricultural operations especially in commercial production where the fear of losing yield has led to management practices that are based on the excessive implementation of chemicals. Though crop yield monitoring has been around for almost two decades, the development and implementation of smarter farm machines, crop sensors, and the software to analyze data that these devices collect have recently become a game changer in yield results.

The technology development over the last few decades has enhanced the position of PA as an emerging management concept. Digital sensors that monitor real world parameters continue to be presented in the market at affordable prices. For instance, digital temperature sensors priced at a few dollars and as small as few cubic millimeters are available for placing at any place in an agricultural field to obtain accurate temperature data, provided they are correctly enclosed and powered [19]–[21]. Also, machine-to-machine communication protocols via electronic components have been revolutionized, among which the Internet stands out as a global communication protocol that can pass data and information between a set of remote computers anywhere in the globe.

The continuous shrink in size and cost of electronic components, such as processing units, modems, and antennas enabled the connectivity of mobile devices and sensors to the Internet as stand-alone objects, which is why the term IoT is used [1]. Now, technology companies have IoT-based solutions for PA which consist of sensors being able to measure the environmental conditions, for instance, at different localized

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spots within a farm; cloud-based platform to collect and integrate data; AI algorithms that extract information and predict patterns; communication mechanism with farm manager over the Internet to notify about conditions, instructions, or required actions.

Bosch Corporation is a global engineering company that has adopted Industry 4.0 in its business and has emerged into the field of agriculture by providing a number of solutions [22]. Industry 4.0 on its own is the digital transformation of industrial markets with smart manufacturing currently on the forefront. It represents the so-called fourth industrial revolution in discrete and process manufacturing, logistics, and supply chain. Although Industry 4.0 has been conceived in the context of manufacturing, many of the technologies applied and converged in Industry 4.0 find their way in agriculture [23].

Bosch's *Deepfield Connect* provides solutions to monitor the agricultural fields for different parameters [24]. Each solution consists of a set of sensors connected directly to the Internet via a communication box which sends the data to Cloud, which in turn sends information and alerts to the farmer on his/her smartphone or computer. Once the set of sensors are installed in one location, it will start sending environmental temperature and humidity information, as well as soil moisture information periodically to the farmer so that unnecessary journeys to the field to check on frost, heat, or dryness can be avoided. To exemplify with asparagus crop, through in-field temperature sensors, the farmer can know the temperature at different layers of the subsoil—an information essential for high yield output. The advantages of such a connected solution extend to the maintenance services that companies provide as they can simultaneously monitor the drop in the performance of an equipment or a component (for instance, a battery) and send timely replacements.

Another organization, Yield Technology Solution, places sensor nodes (a group of environmental and soil sensors) at different locations in an agricultural field that communicate with one gateway over local communication system [25]. The gateway, in turn, connects to the Internet to store and process data in the *Microsoft Azure* cloud. Their system measures microclimate data from around the farm and uses AI and data science to provide information that helps in making decisions—e.g., when to plant, harvest, irrigate, feed, and protect crops. The system builds a detailed picture of the farm's microclimate across a range of conditions and delivers these insights to the farmers as current and future predictions.

In Japan, Bosch has launched *Plantect*, a solution targeting greenhouses, in which one farmer can connect a set of sensors located in different greenhouses within certain proximity to be connected locally to a single gateway which is connected to the Internet [26]. From the information received about the changes in environmental conditions in the greenhouses, Bosch employs cloud computing and AI to predict disease breakouts and advice on pest control management for individual greenhouses. Such a solution aims ultimately to optimize the usage of plant protection products by spraying fungicide, for instance, which contributes to the PA management of optimizing spraying. Although the solution is available now for tomato greenhouses, it should be straightforward to expand this system to other crops via development of specific prediction models for each disease while using the same hardware to collect and visualize data.

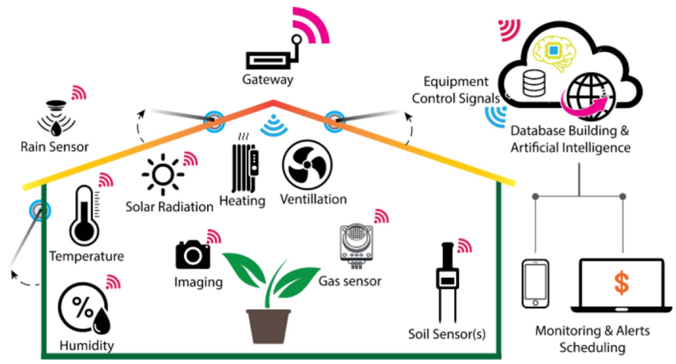

Fig. 5. IoT-based monitoring and control of greenhouse cultivation environments. The greenhouse environment is monitored using a variety of IoT-based sensors, and the automated control is implemented through heating, ventilation, or opening of windows using actuated motors.

For greenhouses, fully automated solutions to control the internal weather and irrigation schedule are available in the market (see Fig. 5). Priva provides such systems where a local communication system between the sensors and actuators within one greenhouse work together to maintain optimum growing conditions for the plants [27]. For instance, temperature and humidity sensors talk to the motors that open and close side windows and ceiling to avoid overheating inside the greenhouse during the day. In cold nights, they can turn on a heater, if the greenhouse is equipped with one, to maintain a minimum temperature to avoid frost. These sensors can also get assistance from a rain detection sensor placed on the roof of the greenhouse, which can actuate closing of the ceilings and maintain the side windows open on rainy hot days, for instance. Also, as the need for irrigation is closely related to light, the irrigation pump is controlled by solar radiation sensor that requests the pump to irrigate when it detects the accumulation of a certain amount of solar energy during the daytime. Lately, with the drop of carbon dioxide (CO_2) sensor prices and the increasing evidence of the correlation between higher CO_2 concentration levels and yield, modern greenhouse control systems include CO_2 sensors which control CO_2 generators that turn on when the photosynthesis activity is high during daytime. Several other new companies are rapidly emerging with distinct solutions to provide greenhouse control and cloud connectivity. Agrinet is a solution that combines greenhouse machinery provided by Nepon Inc. and information and communication technology (ICT) provided by NEC Corporation to enable monitoring and controlling the equipment in the greenhouse remotely [28], [29].

Similarly, E-Kakashi, which was launched by Softbank in 2015 as a sensor box to monitor greenhouses [30], was upgraded into a platform after Softbank teamed up with CKD Corporation and Ericsson [31]. The platform not only keeps constant watch over fields and greenhouses but also control the environment inside the greenhouse. The sensors monitor parameters, such as temperature, humidity, and CO_2, and the machines in the greenhouse are connected to the

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cloud via the Softbank's NB-IoT cellular network. The PS Solutions' e-kakashi platform applies AI to adjust equipment based on environmental data and Ericsson IoT Accelerator powers the device onboarding and data management. Finally, CKD corporation's electro-pneumatic devices allow machinery to be controlled remotely. Accordingly, E-Kakashi can make appropriate adjustments to machinery, such as fertilization, irrigation, and greenhouse ventilation systems. Whenever and wherever he/she wishes, the E-Kakashi user can access and interact with the system using a smartphone, tablet, or computer. The farmer can modify the AI-based standard settings to apply their personal know-how.

Finally, John Deere, the largest agricultural machinery manufacturer in the world is estimated to have deployed several hundred thousand connected machines in the field since 2012. The company estimates that their IoT data collection and automation has boosted yield and reduced costs by $>10\%$ for farmers [32]. The IoT device installations in the agriculture world is predicted to increase from 30 million in 2015 to 75 million in 2020, with a compound annual growth rate of 20% [33]. Several large public–private EU consortia are involved in assessing the benefits of IoT and big data application in agriculture, dairy, poultry, and meat production. An EU sponsored project named DataBio (Data-Driven Bioeconomy) is being carried out to understand the benefits of big data technologies in the raw material production from agriculture, forestry, and fishery/aquaculture for the bioeconomy industry to produce food, energy, and biomaterials, responsibly and sustainably [34]. Likewise, the project IoF 2020 (Internet of Food and Farm 2020) funded by the EU Horizon 2020 and coordinated by Wageningen University, dealt with the "Farm of the Future," trying to translate and adapt the "Internet of Things" technologies to the farm's environment [35].

B. Advances in Intelligent Farm Machinery

The traditional farming equipment companies are engaged in designing of smarter equipment that can integrate with computing environments, connect to IoT devices, smart tractors, and pumps, capable of sensing their environments and responding in real time to anomalies. In recent years, attempts to build agricultural autonomous systems for implementing PA techniques have significantly increased and being implemented by many startups in farms. Cameras have followed the same trend of environmental sensors of becoming smaller and cheaper. Their ability of collecting spatial and spectral data made them subject of research although the need for high spec processing units in comparison to other sensors was one of the main initial concerns for its application in real-time conditions. However, this has changed in the recent years as powerful processing units are widely accessible.

The high cost of applying herbicides and the increasing awareness about the impacts of excessive usage of chemicals on the environment and human health, are driving the efforts to implement cameras as sensors in the field of agriculture to detect weeds. There has been traditionally, two approaches to control weeds, which are chemical and mechanical. In principal, mechanical control has the advantage of being environment friendly but labor intensive whereas chemical control has the opposite features. Recently, some startups have emerged as providers of intelligent and autonomous weeding machines based on cameras for sensing weeds in the fields. We will provide a few examples of recent commercial developments in this area.

Garford Farm Machinery has developed a tractor propelled weeding machine (marketed as *Robocrop in-row weeder*) that consists of machine vision, control system, and weeding mechanism [36]. The main feature of this machine is that it mechanically removes weeds which are located within the rows. This is achieved using a weeding mechanism that rotates around each plant in a spiral trajectory. The plant in turn is detected using RGB color cameras whose data are processed within the machine to determine the center of the crop around which the mechanism will rotate. It was originally developed for use on transplanted crops, such as lettuce, cabbage, celery, etc., but it can be used for most crops that have regular plant and row spacing as long as the plant foliage is separated from the next plan [36]. It can be used on most crops that are planted with regular plant and row spacing where the plant foliage is clearly separated from the next plant.

Deepfield robotics of Bosch have developed and tested an autonomous mechanical weed controller that uses GPS antenna to be self-guided within the field and cameras to distinguish crops, such as sugar beet, from weed. The robot whose weeding mechanism lies underneath the machine can work also at night under artificial lighting conditions [37]. This autonomous vehicle was designed to target weeds in the cultivation of sugar beets—a crop of high economic value in Germany.

Blue River Technology, a start-up recently acquired by John Deere, has developed yet another type of weed control machine that also uses cameras, computers, and AI to distinguish crops from weeds [38]. The tractor-propelled machine currently operating on a limited basis in cotton weeding uses chemical methodology to combat weeds by specifically spraying herbicides on spots where weed is present. The main advantage of this technology is reducing the quantities of chemicals used in agriculture which will bring economic and environmental advantages.

Besides weeding, there are trials to apply the vision technology in orchard harvesting operations which are characterized by labor intensity and time sensitivity. Typical examples of these trials can be found in apple and kiwi fruit harvesting. The main challenge in automating orchard harvesting is that the fruits grow in usually an unstructured environment. Unlike weed, whose distance from the machine is estimated by the approximately constant distance between the machine and ground, the location of fruits on tree cannot be predicted. Also, the sceneries surrounding fruits contain more noise than weeds whose background is limited to other plants and soil. This makes developing commercial harvester a real challenge despite the need for such machines for labor saving and optimizing yield.

In academic literature, research tackling apple recognition and picking is available since the early 21st century as Bulanon [39] developed a machine vision software to detect

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the location of apples on trees. Likewise, research of robotic arms and effectors started to take place relatively at the same period as Setiawan *et al.* [40] developed a gripper that can pick apples without harming the skin. Apple fruit recognition on trees continued to develop as Bulanon *et al.* [41] developed a real-time detection system, Mao *et al.* [42] developed a stereo vision to detect also the distance between the machine and apple to be harvested, and Kong *et al.* [43] used least-square support vector machine to improve accuracy and speed of stereo vision in detecting apples. Robotic arm and end effector research continued to improve accuracy and speed of gripping and detaching apples from trees [44]–[46]. Silwal *et al.* [47] reported the design, integration, and field evaluation of a robotic apple harvester able to detect and pick 84% of the apples with an average picking time of 6 s per fruit.

Kiwi fruit recognition system based on imaging, for future robotic harvester, has some advancements in academic research. In order to overcome the problem of noise caused by the variation of ambient light, Fu *et al.* [48] suggested harvesting at night using artificial lighting to minimize the chance of kiwi fruit misclassification. Unlike apples, kiwi fruits tend to cluster in groups which makes "visual individualizing" an essential feature of any kiwi fruit picking robot; this was tackled by Fu *et al.* [49]. However, issues, such as insufficient success rate in the detection and slow recognition time are two challenges that remain to be tackled before a commercial product could be developed. Despite the slow progress in developing the vision system for robotic orchard fruits picking, investment in this technology is expected to continue as the need to replace manual harvesting is becoming increasingly urgent in countries, such as the United States, Japan, and China.

C. Low Altitude Spectral Imaging

Healthy agricultural plants normally reject much of the infrared spectrum. However, when facing a crisis (diseased/stressed) plants tend to absorb more infrared light. This information is useful for identifying plant infestation, nutrient, or moisture deficiency. Similarly, the greenness of an agricultural field (related to the chlorophyll content of the crops) usually correlates with the nitrogen supply. Traditionally monitoring of field and agricultural conditions (such as crop health, and coverage) was carried out using low-resolution satellite-based remote sensing techniques that measured the vegetation cover over the scales of counties or states. Such methods allowed to get country-wide insights about the yield were of little use to farmers. To overcome the issues arising from low spatial resolution and make spectral imaging techniques accessible at individual farm levels, low-altitude manned vehicle-based spectral imaging was adopted as a solution. This approach was somewhat useful considering that the spectral cameras operating in the infrared region were bulky with a big footprint. With the advancements in spectral imaging technologies, the size and weight of spectral cameras has drastically decreased, and now these could easily be mounted on drones or quadcopters. The most notable advancement with respect to spectral cameras is the availability of compact palm-sized snapshot hyperspectral imagers. These have a much lower footprint and weight compared to push broom (or line-scanning hyperspectral imagers) and are also less expensive.

Data companies are now gathering aerial images of standing crops in farms using hyperspectral and multispectral cameras mounted on manned or unmanned aerial vehicles (MAV or UAV), e.g., quadcopters and drones. Spectral cameras capture image stacks at several wavelengths, with loosely up to 10 bands referred as "multispectral," and over 10- "hyperspectral." Some imaging service providers couple multispectral cameras in nonvisible regions with high resolution R-G-B (visible) cameras. The images from spectral imaging systems are generally taken at sufficiently high resolution (from meter scale to even centimeter scale), but generally downsampled (smoothed) for delivery of practically useful results.

Spectral images of vegetation show considerable variation due to the heterogeneity of natural conditions of the fields (e.g., hydrothermal, soil, and geomorphological) and the agricultural systems (tillage methods, irrigation, use of fertilizers, herbicides, pesticides, etc.) [50]. Using ML algorithms applied to the imaging data sets and incorporating environmental variables, data analysis platforms can generate insights about various indices of importance to crop growth and quality. Examples of such insights include vegetation index, weed cover, pest infestation, waterlogging, yield monitoring, nutrient deficiencies, and maps for variable rate application. Such information is generally gathered by flying the drones and imaging the fields between 2 and 3 times in a cropping season. Eventually, time-series analysis of imaging data to assess the effectiveness of agricultural practices and self-learning techniques for improvement may also be included into the data analysis in some systems. A notable example of the "data analytics as a service" business model for the drone-based hyperspectral imaging of sugarcane and soybean fields is the Swiss start-up, Gamaya (www.gamaya.com). Gamaya employs crop, variety, and region-specific analysis of hyperspectral imaging data (with 40 bands) using crop models and AI to produce detailed information on crop phenology and physiological traits.

IV. Food Supply Chain Modernization

The United Nation reports that one-third of the world's food is thrown away each year, which adds up to $750 billion that is completely wasted. That means that about 28% of the world's agricultural land is used to produce food that is eventually wasted. The supply chain management in a food business is very challenging owing to the need for advanced control systems for coping with perishables, fluctuating supply–demand variations and narrow food safety, and sustainability goals. Consequently, the use of IoT networks involving humidity, temperature, light, and microbiological and product quality sensors for real-time monitoring of products in transit is useful for the food industry in rescheduling, recalling, or taking appropriate actions. According to a report by Zion Market Research, the global AI application in the supply chain market stood at $491 million in 2017

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and is projected to reach about $6548 million by 2024, at a CAGR of around 44.76% between 2018 and 2024 [51]. An exhaustive review of the role of IoT in supply chain management, in general, has been made by Ben-Daya *et al.* [52], while one specific to agri-food industry is presented by Lezoche *et al.* [53].

Considering that food supply chains extend over wide geographical areas and are vulnerable to many global risks, IoT could help in minimizing the risks. Recently, the virtualization of the food supply chain through IoT and an information systems architecture was successfully demonstrated for a fish export business from Norway to The Netherlands [54]. In their paper, the team provided ample arguments to show that supply chain virtualization through the integration of real-time product observations (via IoT devices), combined with business processes provide rich representations of the objects and its context. Such virtualization will enable stakeholders to act immediately when deviations are observed (e.g., temperature fluctuations leading to product quality change). The essential features of the virtual IoT-based supply chain include free exchange of logistics information, and functionality for intelligent analysis and reporting of exchanged data to enable early warning and advanced forecasting [55].

A more generalized approach to virtualize the supply chain stages has been demonstrated by a group from Italy, who developed an IoT-based tool in LabView to integrate the entities involved, the product flows and the food ecosystem boundaries [56]. The authors concluded that IoT-based virtualization of food supply chain will allow a dramatic reduction in the inefficiencies, costs, emissions, and social impacts. To provide an example of the power of virtual (or cyber–physical) supply chain systems, let us consider a food truck equipped with temperature, humidity, and location (GPS) sensors carrying soft berries (say, strawberries). Through virtual supply chain systems, logistics providers can accurately track the location of the food truck at any point in time. Now, in the unlikely event of food shortage at a different location, the nearest truck can be rerouted to the new destination. Alternatively, if a temperature fluctuation is noticed, such that it may affect the shelf life of the berries, the truck can be diverted to the closest market for immediate sale at discounted price. Thus, IoT technology could not only help the growers or help to meet the product demand, but also prevent food wastage.

The destination of the food truck in our example can also be decided based on customers identified through social media platforms or mobile phone applications. Food Cowboy (www.foodcowboy.com), for example, uses a mobile app to allow truckers and food companies to reroute imperfect produce to charities, spoiled produce to composting sites, and surplus food from local restaurants to food banks and soup kitchens. Many other online interactive maps linking places with food surplus to charities and people who need it, and apps connecting neighbors for food sharing have also evolved. However, the safety of food and legal implications in such peer-to-peer food sharing platforms remains unclear.

The past decade has seen a significant rise in the use of machine (or computer) vision to efficiently and timely execute repetitive tasks in supply chain, including quality control inspection. The supply chain industry is increasingly relying on automated guided vehicles (AGVs) based on AI, machine vision, and navigation technologies [e.g., simultaneous localization and mapping (SLAM)] for automated material handling in manufacturing [57], [58]. Machine vision has helped companies in implementing end-to-end automation [59], and now the application of AI for its integration with supply chain for individual product tracking is being explored. In recent times, grocers are using inventory barcodes and sensor-collected data to determine the rates of inventory consumption, such that stocking levels can be set to meet but not exceed demand. Radio-frequency identification (RFID) is another sensor technology that has seen an exponentially rising adoption by producers, food processors, agri-food supply chain industry, and merchants to establish traceability systems [60].

In a related context, the introduction of counterfeit products into the market is a big challenge for food and pharmaceutical companies. Similarly, "product diversion," i.e., the movement of a product consignment to a location not originally intended, though uncommon, also occurs sometimes. While technologies, such as barcodes and holograms have been in use for decades heretofore, the minor deviations during the print of barcodes has been exploited as a unique fingerprint by the company, Systech International (www.systechone.com). Their unique process uses the microscopic differences (arising from production environment variables) in the same barcodes on multiple products as a unique fingerprint. Thus, this fingerprint data retrieved in the manufacturing facility using a computer vision system can be used to track individual products throughout the supply chain, thereby preventing product diversion. Furthermore, this data can also be used for validation of the product by retail outlets and consumers using applications owned by brand owners, thereby helping to prevent counterfeiting.

Should IoT integrated with cloud computing take up the space of connecting movement of raw materials and finished products to the automated databases, the process of documentation and regulatory compliance will become much easier and efficient. Next, it will be interesting to note that customers are more and more demanding in terms of food choice—portion size, shape, flavor, color, price, and the level of service [61]. IoT and AI could serve as enablers for "end of line" and "last minute" customization technologies for the food industry [62]. Thus, in future, an Internet-based food purchase order received from a customer with several peculiar specifications could automatically be redirected to the robots on the production line for "last minute" customization. In fact, it will not be exaggerating to state that IoT and AI-enabled customization-oriented production will be one of the significant achievements of food industry 4.0.

Despite the projected potential benefits, the integration of IoT with business processes is still at a very early stage of development in food supply chains and food industry, in general. Several challenges with respect to granular data alignment exist when creating end-to-end digital thread from farm to consumer. It is to be noted that supply chain systems are very cross-functional and additionally involve data sharing between

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companies/business entities. As such, cross-entity data sharing becomes much more challenging in the agri-food sector where data from farms is currently very limited. Even when considering large food manufacturers and enterprises, they rely on co-packers or outsource to contract processors, meaning a third-party holds all the production facility data, that too under different naming conventions. Moreover, many raw agricultural materials are often sourced by industry in the developed world from developing or under-developed regions, where there often is a lack of data awareness. The process of including most partners into the AI system is crucial to avoid underperformance of the algorithms due to missing data and prevent loss of opportunities for optimization. Next, most agricultural products undergo dynamic changes in their quality and therefore pricing. This additional layer of high uncertainty adds difficulty in tracking such data in real time as compared to other supply chains. The development of appropriate frameworks for reaping the benefits of IoT, big data, and AI needs immediate attention for its success.

V. Web and Social Media Analysis

The massive rise in the number of computing and mobile devices in use has resulted in an exponential growth in data volumes over the Internet. It is estimated that every minute of Internet activity in 2016 resulted in 3.3 million Facebook posts and 448 800 tweets, 65 972 pictures, and 3.8 million searches on Google [63]. Social media data can come from a variety of platforms, such as blogs, discussions, or comments on websites (e.g., news pages), microblogs (Twitter), collaborative projects (e.g., Wikipedia), social networking sites (Facebook and LinkedIn), and content communities (e.g., YouTube and Instagram) [64]. Typical examples of metrics that can be drawn from social media content created by users, include followers, shares (or retweets), likes, comments, mentions, and metadata associated with the clicks. The metadata associated with users' activities could include information, such as age, nationality, education, profession, geolocation, and more, depending on what the user had preferred to share.

Briefly, social media data refers to the information gathered from social networks that reveals how users share, view, or engage with the content or profiles created by a user or organization. As the most common example, Facebook pages of companies "liked" by users results in the user receiving brand page updates and contents in their news feed. This way brands can interact with those who like or follow their pages and *vice versa*. Nearly all food companies have a social presence with a huge number of people who follow their Facebook pages and thus, are part of the social interaction and data creation process (see Fig. 6). The aim of a typical social big data analysis is to retrieve valuable chunks of knowledge from the huge amount of complex user-generated content (often linguistically or graphically expressed), and help agencies, industry, or stakeholders make informed decisions.

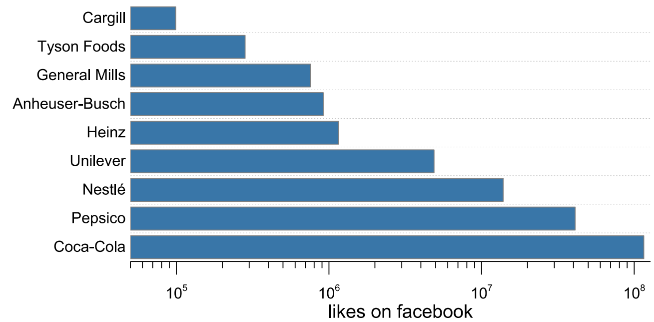

Fig. 6. Number of people liking the Facebook pages of major food companies. Note that the bars are a sum of all filtered company pages (but not brands) that are verified by Facebook. Data retrieved on July 7, 2019. The numbers could include repeated measurements when a user has liked more than one page.

A. Open Innovation and Renovation via Crowdsourcing

Innovation refers to introducing something as a novelty, which could be in terms of product, market, service, or business model. The concept of open innovation encourages companies to acquire outside sources of innovation to improve product lines and shorten the time required to bring products to market. In addition, it also emphasizes on marketing or releasing internally developed innovations which do not fit the company's business model but could be effectively used elsewhere [65]. Several reviews have dealt with various aspects of open innovation within the food industry [66]–[69].

Data mining via ML techniques are increasingly being employed to identify the most preferred and disliked features of existing products, by analyzing thousands of consumer comments on websites like Amazon, eBay, Facebook, YouTube, and other e-commerce website. Insights generated from natural language processing (NLP) and sentiment analysis (see Section V-B) of social media and e-commerce data can guide development of new products or technologies as per consumer preferences, helping determine important design decisions to meet customer needs more accurately. This approach arms industry with the information to make future products highly innovative, consumer friendly, resilient, and respectful of market requirements. Note that the intellectual inputs for the new or improved product in such cases are fundamentally crowdsourced through online platforms.

Besides unsolicited user-generated content, it is worthwhile noting that businesses also adopt Web media as channels for building and distributing information and values. Social platforms are increasingly being leveraged as grounds for connecting, interacting, and collaborating with consumers. For example, in recent years multinational food companies have been engaging consumers in co-creation via social media marketing campaigns for the development of new flavor and texture for their products. When users respond with a unique hashtag or media handle to the campaign, all user responses with its associated can be gathered to obtain a huge corpus of information. Analysis of the textual data collected overlaid with user-related metadata (such as geolocation, age, profession, time of content creation, etc.) from social campaigns

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can be a valuable way to both gather insights and to market segmented brands.

Finally, it is worthwhile mentioning that Web scraping and big data analysis is also being employed by many enterprises to compare the prices of the products and assess where the sales price of your products lie within that product category in the e-commerce world. In conclusion, enterprises should consider big data analytics as one of the tools in their research toolkits and learn from the successful programs leading the way. By understanding what consumer's value and engaging in active dialogue and interaction, companies can develop superior value propositions that are more relevant to their target audience.

B. Sentiment Analysis

To determine the sentiments that consumers associate with a given product, brand, or company—be it positive, negative, or neutral—big data analysts perform "Sentiment Analysis" on the huge corpus of text data from social websites, merchant sites, and blogs. In fact, several companies have either assembled or are in the process of assembling "digital acceleration teams," also called "social listening teams," to monitor social media sentiments at high frequencies (sometimes even at hour intervals). For scraping large-scale reviews at regular intervals several new startups around the concept of "Data-as-a-Service" provider (DaaS) have mushroomed in recent years. DaaS providers have the computational infrastructure for high-quality data extraction from e-commerce and social media websites without interruption.

The first aim of most sentiment analysis workflows is to overcome the information barrier from social slang and lingos and nontextual expressions (emojis) and language. This is usually followed by matching of user-generated words against a prebuilt, preclassified custom lexicon (dictionary of words). Using tools for real-time analysis of streaming social data, the digital teams of companies can detect upcoming challenges and opportunities in a timely manner. Companies can then engage with the concerned parties—consumers, organizations, suppliers, or government bodies to harness the opportunity or resolve the challenge. As an example, a food industry can monitor the changes in sentiment scores associated with a reformulated product and thus assess the success of the reformulation to overcome the negative sentiments.

C. Personalized Nutrition and Health Advice

Nutrition can be a highly complex and individualized facet of life. What works for one person may not be effective for another. The Internet has allowed the proliferation of advice relating to nutrition and health. It has been observed that between 55% and 67% of American adults search for health and wellness information on the Internet, and 20%–34% of them use social media [70]. In a recent work, it was concluded that young adults are generally open to receiving healthy eating and recipe tips through social media [71]. Thus, it becomes clear that with an expanding population getting access to Internet, nutritionists, health educators, and food companies can take advantage of social media campaigning and consented social data collection for personalized nutrition and health recommendations.

Social media is increasingly being exploited as a platform for distributing nutrition and wellness campaigns, increase exposure to evidence-based health messages and encourage users to participate and engage with interventions [71]. In an exemplary multichannel social marketing campaign named Food Hero, a focused target audience in Oregano, USA were provided with nutrition-related messages [70]. The audience were messaged with evidence-based research findings to promote an increase in the amount and variety of vegetables and fruit consumed. The metadata of users and their activity were used to understand the audience's learning behavior, tuning the content for effectiveness and long-term planning. While, cloud-based frameworks for effectively managing health-related social big data has recently been proposed and demonstrated [72], such frameworks are yet to be reported in the nutrition space. It is also to be noted that the effectiveness of social media-based targeting could become limited when users do not wish to share their personal health or nutrition-related information [71].

Freeman *et al.* [73] reported that young adults are being bombarded with messages about energy dense, nutrient-poor (EDNP) food, and beverages on social media platforms, that are sponsored by food industry organizations with commercial interests. A strict check on such conflicts between public interest and commercial interests through appropriate regulations is highly desirable. Unfortunately, governments around the world are yet to define and frame proper guidelines and regulate the content released on social media. It will be interesting if the academic world can come together with appropriate social media analytics to identify and classify the advertisements based on cleverly chosen metrics. Moreover, the fact that few enterprises store and use the data of consumers and their interactions with products for intensive marketing and influencing the decisions, is a matter of concern to many consumers. Governments need to regulate the privacy of data of its citizens and consumers, taking the European Union's recently enacted general data protection regulation (GDPR) as a good example.

VI. Food Quality and Authenticity

In recent times consumer awareness toward food composition and quality has surged owing to an increasing awareness about healthy lifestyle and technological advancements in food science and technology. Moreover, food safety regulations demand detailed labeling of product composition along with strict quality monitoring [74]. In this context, UV-Visible-near infrared spectroscopy (UV-Vis-NIRS)-based IoT sensors and big data are evolving as important players in food composition, quality, and food safety assessment areas.

A. Spectral Fingerprinting of Foods

UV-Vis-NIRS is an extensively researched technology with regard to food composition and quality predictions [75]–[78]. Numerous studies have been conducted using UV-Vis-NIRS

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for evaluating food composition and quality with the aid of chemometrics [79]–[81]. The review by Reid *et al.* [82] discusses the successful application of spectroscopic techniques, such as UV, NIR, MIR, visible, and Raman for food authentication. Another review by Porep *et al.* [83] emphasizes on the studies dealing with online application of NIR spectroscopy for industrial processes in the food industry. Similarly, the review article by Dixit *et al.* [84] contributes a detailed discussion on the various studies regarding applications of NIR spectroscopy for online monitoring of meat and meat products. UV-Vis-NIRS is a rapid and nondestructive technology that has motivated the food industry to use it for quality monitoring purposes. The UV-Vis-NIR region covers the wavelength range from 200 to 2500 nm. UV-Vis spectroscopy typically yields broad, overlapping bands; spectroscopic measurements for most liquid and gaseous samples rely on the Beer–Lambert Law. Spectra of solid samples are usually recorded in the units of reflectance (R) or percent reflectance (%R). Color measurements are conducted by utilizing the transmittance and reflectance data for liquid and solid samples, respectively [85]. NIR spectroscopy is based on molecular vibrations produced by functional groups containing hydrogen atoms: C–H, N–H, and O–H. These molecular vibrations generate spectral signatures that are specific to a compositional attribute, ingredient, adulterant, or a contaminant. A characteristic UV-Vis-NIRS system consists of a light source, spectrophotometer, and a computer for data acquisition. The light source illuminates the sample, which is then either reflected, transmitted, or diffusely reflected followed by its detection via an interferometric or a dispersive system [86].

One of the major issue with NIR spectra is the noise generated from non-linearities introduced by light scattering phenomenon, such as Mie scattering and optical scattering [87], which necessitates the use of statistical and mathematical routines. This branch at the interface of data science and chemical physics is widely known as chemometrics. Chemometrics plays a significant role in overcoming the challenge of non-linearities and thus helps in extracting useful information from UV-Vis-NIR spectra. Typical processing of spectral data involves enhancing the signal-to-noise ratio (SNR), pattern recognition/classification/quantitative predictions: preprocessed spectral data are subjected to various multivariate statistical methods for building either qualitative or quantitative models [85]. In an IoT context, spectral data acquired is typically transferred to a remote server where spectral processing is performed while validating the data over prebuilt calibration models. This approach allows utilizing large spectral databases and trained models for near real-time assessment of various food materials.

B. Miniature Spectrometers as IoT Sensors

Until some years ago, UV-Vis-NIRS systems were bulky, immobile, and accessible by laboratories only. However, recent developments in microfabrication and miniaturization of optical systems via holographic optical elements (HOEs) have empowered the creation of "palm-sized" spectrophotometers which are compact, mobile, and pocket fit, and can be connected to the Internet for real-time data transmission to remote servers. Organizations like Hamamatsu [88], Texas instruments (Texas Instruments Inc., Texas, USA), and consumer physics [89] have developed such "palm-sized" spectrophotometers which can be used for real-time quality checks, agri-food authentication, and identification. In fact, Hamamatsu Photonics has developed the world's smallest "fingertip size" micro-spectrophotometer which is ultracompact, lightweight, and low-cost device. The micro-spectrophotometer offers measurement in the visible wavelength range and can be used for applications, such as color sensing, point-of-care testing connected to smartphones, and other types of portable measurement.

The large amount of data necessitates remote data analysis on powerful computers for receiving real-time insights regarding the product on compact UV-Vis-NIRS devices or say, mobile phones of a consumer. Thus, such technologies offer an opportunity to develop real-time composition and quality assessment methods. To exemplify the significance of emerging UV-Vis-NIRS IoT platforms, let us consider a typical quality monitoring scenario in a flour storage facility. Traditionally, to check the authenticity of wheat flour, a safety inspector would perform sampling followed by time-consuming offline analysis. However, the situation demands for a rapid decision at the storage facility. Similar situations could arise when real-time decisions are to be sought regarding quality or authenticity of agri-food products. The duo of UV-Vis-NIRS as IoT sensors and big data methods can provide a robust solution to such situations by availing real-time product information, such as detection of adulteration, allergen detection, geographic origin, and composition.

Tellspec is a data company which has combined NIR spectroscopy, bioinformatics techniques, and learning algorithms for real-time analysis of consumer foods at the molecular level [90]. The system includes Tellspec's food sensor which is based on the technology from Texas instruments, a cloud-based patented analysis engine and a mobile app that work together to scan foods, identify ingredients, and provide details about the food scanned. Tellspec has conducted various studies with respect to food quality, authentication, and characterization. Tellspec evaluated a handheld NIR scanner for simultaneous prediction of melamine and urea in wheat gluten samples [91]. In another study, the handheld NIR scanner was successfully employed for the detection of beef aging combined with the differentiation of tenderloin and sirloin [92].

SCiO is a technology developed by Consumer physics which combines two integrated technological components: 1) the sensor and 2) the cloud [89]. The SCiO sensor's optical head is only a few millimeters in size; provides high sensitivity and accuracy. It has low power consumption and zero warm up time which makes it highly responsive and extremely efficient. The SCiO cloud provides the analytical processing power and hosts the material databases. The SCiO cloud hosts the chemometric models and algorithms that analyze spectra and convert them into useful material data. Chemometric models run on a linearly scalable architecture, which allows to provide fast

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response times to a practically infinite number of users and devices.

C. Spectroscopy and Sensor Fusion

The intelligent convergence and processing of data from multiple sensors for making a process autonomous, is commonly referred to as "sensor fusion." The results of efficient sensor fusion are almost always better than those obtained from the interpretation of data from individual sensors.

In a recent EU-funded project named "MUSE-Tech," the fusion of state-of-the-art sensing technologies (photoacoustic spectroscopy, quasiimaging UV-Vis spectrometry, and distributed temperature sensing) was demonstrated to improve the handling of raw and in-process materials in food manufacturing. The project developed a multisensor device that can react in real time to variations in raw material and processing conditions to optimize the quality and safety of processed foods. For instance, one leg of the project focussed on reducing the risk of developing the toxic polar compound(s), such as acrylamide in starchy foods (e.g., potato chips) during cooking by specifying the guidelines for frying time and temperature. A computer vision system was developed for online inspection of potato chips and frying oil quality with industrial settings. The chips were classified according to color, oil uptake, polar matter, and acrylamide levels using NIR and imaging sensors. The relevant data sets from the network of such sensors, the IoT, can be clustered to a cloud portal and mined to assist in regulating quality standards [93] within the Industry 4.0 framework.

The future of agri-food quality and authenticity looks bright under the influence of IoT and big data. Advancements in microfabrication and miniaturization of optical systems have led to the development of "palm-sized" or even "fingertip-sized" spectroscopic devices. Moreover, constant improvement in chemometrics has helped in extracting further relevant information from the acquired spectral data. Overall, UV-Vis-NIRS-based IoT, in collaboration with big data offers a valuable and robust quality and authenticity monitoring tool for the agri-food sector.

VII. Food Safety

A. Big Data and Foodborne Outbreaks

Food safety from farm to fork has emerged as an international priority for all the stakeholders around the globe. The recent foodborne outbreaks of fresh produce in the United States, with two large occurrences of *Escherichia coli* contaminated romaine lettuce in 2018, a lot of food (which also included large quantities of the safe produce) was dumped to protect public health [94]. Knowing that the demand for food is expected to increase by 50% from 2012 to 2050 [95], the current practices to defending public health from foodborne outbreaks might not be the viable option of the future. Realizing the significant economic impact of outbreaks, technological advancements and integrated measures from informatics can play a crucial role in the mitigation of food safety risks and prevention of future outbreaks, saving millions and lives of many [96].

A large amount of food safety data is created each day within the food industry and identifying means to extract robust information from different sources would support microbial risk assessment, prevention of outbreaks, identification of trends through pathogen surveillance; all that will facilitate food safety outcomes and decision making [96], [97]. Real-time monitoring of food during storage and transportation, digital labeling methods that are easy to synchronize to cloud information and enhanced traceability through blockchain are some of the many advantages that informatics can contribute to the future of food safety.

The key points in handling an outbreak are primarily focused on protecting public health and minimizing the damage. It includes identification of hazard, effective containment, and the mitigation of the risk in a limited time period. To limit the impact on public health, U.S. Centers for Disease Control and Prevention (CDC) has Web-based tools, FoodNet, PulseNet, and GenomerTrakr to quickly identify and contain foodborne illness outbreak. The FoodNet is the Foodborne Diseases Active Surveillance Network that tracks trends for infections transmitted commonly through food; PulseNet uses DNA fingerprinting to identify patients and find clusters of disease that might represent potential outbreaks; and GenomeTrakr is a FDA managed database that contains information of foodborne bacterial germs from food products and the environment, with 27 domestic and three international laboratory sites [98]. The pathogen is isolated from the samples collected from sick people and DNA fingerprinting is conducted to get the *Whole Genome Sequence* of the pathogen. The data collected from 83 laboratories (PulseNet Network) in the United States is analyzed and matches are detected using foodborne disease outbreak surveillance system (FDOSS). CDC's division of Foodborne, Waterborne, and Environmental diseases extracts the information from these Web tools using the big data analytics and identify trends in foodborne illnesses [99]. Also, CDC has an international database called PulseNet International and partners with Canada, Europe, Asia Pacific, Africa, Middle East, Latin America, and the Caribbean, to share whole-genome sequencing (WGS) information through global laboratory networks and support foodborne disease surveillance and outbreak response [100]. PulseNet impacts public health by identifying the fingerprints of the pathogen (whole-genome sequence) from the sick people and find clusters of similar information to isolate an unrecognized outbreak [101].

WHO has recently ventured toward big data analytics to support decision making in global food safety outbreaks via a food safety platform called "FOSCOLLAB" [102]. This platform encompasses data (structured and unstructured) derived from evaluations of joint FAO/WHO expert committee on food additives (JECFA), joint FAO/WHO meeting on pesticide residues (JMPR), and global environment monitoring system (GEMS) databases, among others to cover multiple segments, *viz.*, animal, agriculture, food, public health, and economics which are integrated and accessible to all stakeholders.

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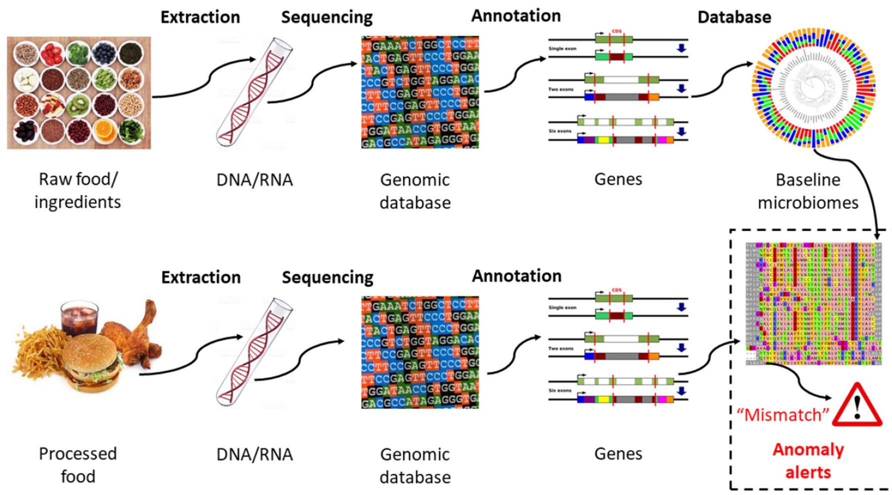

Fig. 7. Process flow to build genetic index of food and its normal microbiome. Adapted from Beck *et al.* [108].

B. Whole-Genome Sequencing

In the recent past, phenomenal advancements have been made in the field of WGS and has gained significant acceptance in food industry in the surveillance of foodborne outbreaks. It is a genomic tool to determine the genetic makeup of microbes by reading the unique DNA sequence of the sample. WGS has replaced the use of traditional microbial typing techniques, including pulsed-field gel electrophoresis (PFGE) and multilocus variable number tandem repeat analysis (MLVA) with superior sensitivity, specificity, and higher resolution to outbreak clustering [100], [103]–[105]. The traditional methods unlike WGS have never been used for real-time surveillance of foodborne illnesses [105]. The process of characterization of DNA isolates from pathogenic organisms is more efficient with WGS, and thus supports the rapid detection of outbreaks and timely containment of illness to protect public health. The microbial DNA sequencing can be done using platforms, such as Illumina, Ion Torrent, PacBio, and Nano-pore [106]. The three commonly used analysis methods used to process WGS data are k-mer, single nucleotide polymorphisms (SNP), and multilocus sequencing typing (MLST) (also called the gene-by-gene-based method), and is used by PulseNet International [100].

Sharing of WGS data among the leading food regulatory agencies of the world will enhance the surveillance and prevention of epidemic diseases and outbreak globally. The United States Food and Drug Administration (USFDA) has pioneered to offer WGS data sharing through GenomeTrakr with other potential agencies worldwide to accommodate regulatory and compliance activities [107]. The European COMPARE project (Collaborative Management Platform for Detection and Analyzes of (Re-) Emerging and Foodborne Outbreaks in Europe) is working on to share WGS data and analysis, to speed up detection and response to human and animal disease outbreaks worldwide (https://www.compare-europe.eu/) [100]. For the complete implementation of WGS-based worldwide surveillance of outbreaks, several challenges need to be met, including technical (WGS sharing, standardized subtyping) and political limitations. The international efforts to minimize the effects of foodborne illnesses and prevent foodborne outbreaks can enormously benefit from WGS-based surveillance, thereby supporting the health demands of the public.

An example of the synergistic impression of genome sequencing and big data analytics on food safety is a collaboration between IBM Research and Mars, Inc., that focused on sequencing and constructing of a genomic database of bacterial species across global supply chains (see Fig. 7 for a graphical summary). The main essence of this project is the building of a genetic index of normal bacterial species that are natural inhabitants of food ingredients and pairing them with genetic fingerprints of food ingredients and their environments to capture the anomalies. Using big-data methods and bioinformatics algorithms, researchers constructed and aggregated terabytes of genomic data to identify the active genes and metabolic processes in the food ingredients. The index produced from this article will serve as a benchmark representing the normal microbial communities of food ingredients with geographical variations. This would facilitate the identification of genomic fingerprints of healthy food, equip food regulatory officials with rapid and precise information to assess the irregularities in food samples that show the presence of spoilage/pathogenic bacteria and design the most appropriate tests and standard operating procedures. Presumably, this will also deliver the critical understanding of anticipated causes of food spoilage/hazards that can be fixed at the point of incidence and allow appropriate strategies to be amended [108].

Next-generation sequence (NGS) is one of the latest advancement in genome sequencing that is widely accepted in food microbiology world for outbreak investigations, food authenticity, and antimicrobial resistance [109]. The new technique uses WGS, metagenomics, and amplicon sequencing (metabarcoding). WGS will answer the phenotypic characteristic of growth and inactivation of an isolate; however, knowing that these phenotypic factors can vary at transcriptional and post-transcriptional level, multiomics approach may

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be the need of future to precisely characterize the pathogen isolates [106].

The vital challenge to the implementation of WGS data analysis and potential opportunities to safeguard the food supply chain worldwide is the privacy of data among the leading companies. Not enough legal measures are in place to protect the companies from regulatory actions, putting reputation, and equity at stake, that ultimately insists companies to limit data sharing. Other challenges include correct interpretation of data, legal infrastructure, and data ownership [106].

Beyond genomic information, there are other equally important factors that can be used to establish the source of contamination. The combination of socio-environmental information and whole-genome sequencing of prevailing and historical isolates were used by Gardy *et al.* [110] to ascertain the point of origin of a tuberculosis outbreak. Although the collected data were not colossal (36 isolates), the variety of data was important which was amplified by social listening and networking with patients. Some investigators applied an interesting approach of proactive geospatial modeling to food logistics to recognize the traders involved in the dispersal of contaminated food [111]. The model encompassed the distribution network of traders, population density, locations, and consumer behavior to predict the probability of food safety outbreaks or recall. In another interesting investigation, the reviews of online restaurant customers [112] were analyzed for keywords pertaining to "food poisoning." The outcome of the study was related to the outbreak control database of Center for Disease Control and Prevention. They concluded that this type of assessments could complement the traditional surveillance systems in providing real-time outbreak information. The potential of IoT to augment food surveillance systems are up-lifting and acting synergistically with big data analytics as a rapid salvage to food safety outbreaks [113]. It is anticipated that IoT would be advantageous to implement a holistic approach in food safety where key drivers, *viz.*, climate change, economy, and human behavior could be combined to envisage food safety risks.

C. Traceability

The inability of the food regulatory agencies to identify the origin of contamination in foodborne outbreaks shatters the public trust in the food supply chain significantly. As an example during the Spinach outbreak of 2006, it took two weeks to isolate the contaminant and ample resources were expended [114]. Another recent instance includes the romaine lettuce outbreak of 2018 where all the lettuce was pulled off the shelves without knowing the origin of contamination. All lettuce was discarded due to inefficient back-tracing by the food regulatory agencies. The FDA issued a recall after 67 days since the first person reported sickness due to consumption of romaine lettuce [94] (see Fig. 8). The inability to trace products comes from inadequate record keeping methods in place, such as the widely accepted "One Up, One Down—OUOD approach." One can only hold responsible the immediate supplier and the immediate buyer up and down the supply chain, and in times of outbreak investigations, it takes

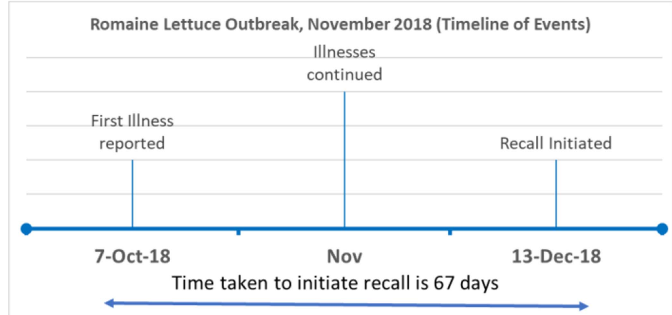

Fig. 8. Timeline of events that led to recalls following the romaine lettuce outbreak of 2018.

days to connect the records and identify the source of contamination. This leads to the degradation of consumer trust and results in significant setbacks to produce growers (such as spinach and lettuce growers). To address this issue, blockchain technology can be introduced. Introduction of blockchain will enable rapid and accurate traceability, reducing cost from food losses and saving precious human lives [114], [115].

Blockchain technology is a success in the cryptocurrency world, since its launch in 2008. Blockchain is known for its digital decentralized ledger system that does not require a trusted intermediary for transactions [116]. The blockchain technology is essentially a database of records stored in the form of "blocks," shared among all members of the group, resistant to data modification, and can be accessed at any time in the future [117]. Similar approach can be extended to a food supply chain where information like production data of food, origin, storage and shipping temperatures, expiry date, etc., can be digitally stored in a database [see Fig. 9(a)]. This will enable the rapid identification of an outbreak or authenticity of food (kosher and organic) [116]. The numerous actors involved in the food supply chain make it challenging to keep records and keep track of food items.

Blockchain can potentially provide solution to this issue and can assist with implementing food safety, food security, and food integrity measures, while bringing transparency and accountability to the supply chain [118]. A study conducted by *Walmart* and IBM to trace sliced mangoes from South and Central America to North America exposed the potential benefits of blockchain, highlighting the significant gap in the current traceability procedures [119], [120]. Two different supply chains were studied; pork in China and mangoes in the USA. The traditional method of traceability took seven days to connect the supply chain from consumer to the origin of the mangoes. However, when the same data were fed to blockchain, it delivered information within 2.2 s [114] [see Fig. 9(b)].

In agricultural logistics, big data analytics could be used to predict the occurrence of food hazards by linking the biotic or abiotic information to the growth and probabilistic occurrence of pathogens and toxicants. For instance, close monitoring of biotic and abiotic conditions in crops field has been reported to help identify the areas of increased incidence of aflatoxins before the harvested crop could enter the food chain [121]. IoT in food logistics, enabled by GPS, RFID, and other sensor-based

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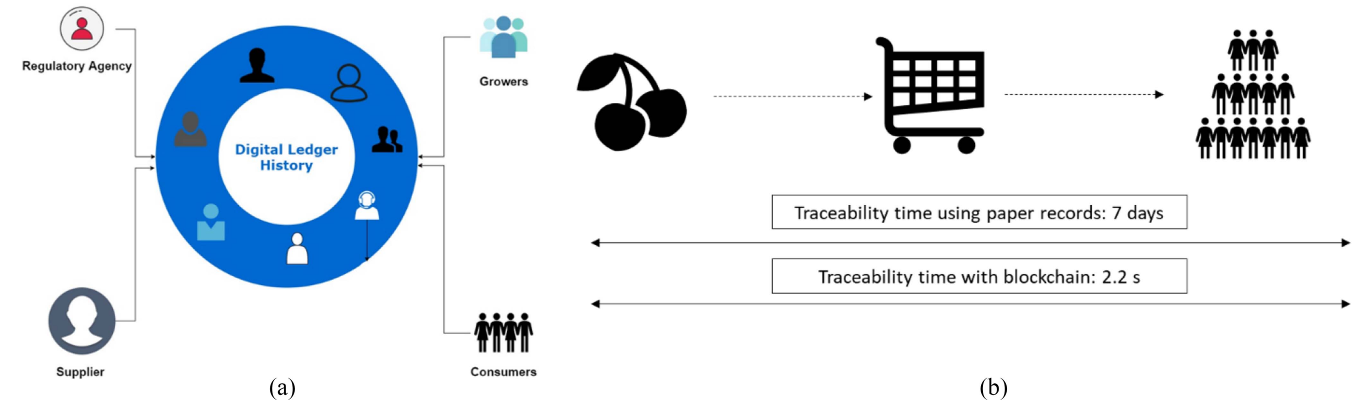

Fig. 9. (a) Concept of blockchain technology as applied to food supply chain for traceability and outbreak detection. (b) Traceability time in the farm to fork chain will be practically eliminated through the implementation of the blockchain ledger.

tracking and traceability, are key to ensure rapid recalls and real-time data collection of food attributes at the site. The Cheesecake Factory, a large U.S. restaurant chain, routinely gathers and transmit data on transportation temperature, shelf life, and food recalls, which is subsequently analyzed by IBM's data analytics solutions before significant information can be shared across its logistic chain [122]. *Walmart* uses a sustainable paperless auditing and record keeping (SPARK) system that automatically uploads data pertaining key food attributes to an online database. This allows *Walmart* to keep a check on food product quality, like internal cooking temperature of rotisserie chickens, to isolate uncooked product for future inspection by health officers and private investigators [123]. In an investigation by Van der Fels-Klerx *et al.* [124], quantitative models and databases were leveraged to forecast the mycotoxin deoxynivalenol (DON) contamination of wheat in north-western Europe. Likewise, a farm-based characterization of pathogens combined with environmental and meteorological data allowed the presence of *Listeria monocytogenes* pathogen to be predicted [125].

VIII. Future Trends, Challenges, and Needs

IoT, Big Data Handling, and Computation: The massive amount of data generated from IoT devices and social media generally demands appropriate infrastructure to store, process, or analyze, and instruct appropriate automated actions based on the insights obtained. Because of the cost associated with such infrastructure, the "platform-as-a-service" business model is becoming increasingly popular. Examples of some of the top IoT platforms on the market today include, Amazon Web Services (AWS), Microsoft Azure, ThingWorx IoT Platform, IBM's Watson, Cisco IoT Cloud Connect, Salesforce IoT Cloud, Oracle Integrated Cloud, and GE Predix. With the cost of sensors projected to plummet and the need for cloud computing expected to rapidly peak, database management, cloud computing, and analytics as a service are expected to be the future business models of choice.

Agriculture: The cost of data acquisition in data-driven agriculture continues to remain very high, thereby significantly decreasing the impact of IoT and AI in increasing agricultural productivity. This situation can only improve through innovations leading to inexpensive sensing technologies, which does not appear to become a reality in the immediate future. As the partnership between the big data technology industry and the farming community progresses, the question of who holds and owns the data will remain a top priority for farmers as well the technology companies.

The use of advanced technologies in agriculture is limited to highly developed countries, while most farmers across the rest of world are struggling to survive. The advanced technologies are generally suited to the needs of large factory farms, like those present in north America or Europe. This implies that Internet-based technologies cannot emerge as influential drivers in changing the global agricultural productivity. Therefore, the success of these technologies in developing and underdeveloped countries can only improved through strong political willpower leading to governmental support to the farmers.

Social Media: Social media and personal level data are slowly becoming the new "most valuable resource" of this era. New challenges are emerging, such as the concerns over data privacy raised by consumers and businesses, cyberattacks, use of bots, and fraudulent social media accounts by anti-enterprise bodies to negatively affect the reputation of companies and promote marketing of counterfeit/fake products on the World Wide Web. Therefore, digital teams of companies must constantly innovate to proactively tackle adverse situations and handle mishaps on social platforms.

Food Supply Chain Modernization: Quantitative studies on the benefits of IoT in supply chain are yet to be carried out. IoT integration with food business processes for control of the supply chain is a challenging topic that needs further study on a case by case basis. In general, IoT implementation in the food supply chain business is being rapidly improved considering that product-level tracking using sensors was a familiar concept to this sector. The decentralized food diversion and consignment redirection based on shelf-life prediction are the new trends which are expected to grow. These developments will help to significantly reduce the food wastage. It is likely

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that end-to-end supply chain traceability in agri-food industry will be achieved in future via technology implementations that differ slightly from blockchain methodologies due to the involvement of several stakeholders and actors, including end consumers.

Food Quality via Spectral Data: Presently, hyperspectral cameras and UV-Vis spectrophotometers are being used more commonly in the food industry for quality monitoring purposes than ever before. Tech startups are producing consumer focussed pocket-size spectral devices considering health conscious mindset of millennials. Miniaturized and faster hyperspectral cameras are being actively designed and developed keeping the needs of the industry in mind. Currently, a pocket-size spectral sensor costs as low as $300, but can be priced at $100 000 for commercial spectrophotometers. The cost of hyperspectral cameras is prohibitively high with starting prices of approximately $20 000 and can reach several million dollars depending on the specifications. Furthermore, the databases of spectral features for foods are also evolving and far from commercial acceptability. While similar issues are being rapidly resolved for field applications in PA, the food industry is significantly lagging. Nevertheless, the demand for spectral technologies is envisaged to continue to grow for food applications.

Food Safety: With the recent change in food safety regulations, focus has changed from reaction and response to prediction and prevention. The current food safety challenges require comprehensive and organized ways to address future foodborne outbreaks with gathering and examining large volumes of genetic information for early identification of food safety issues. Future food safety challenges insist stakeholders to develop better methods of tracing food supply chains protecting food and public health. Ensuring the safety of food would be key to the future of sustainable agriculture meeting high food demands of the world. Science-based decision making and the use of advanced technologies (WGS, blockchain, and digital process data logging) would play a crucial role in gathering critical information from around the world and connecting various disease and outbreak databases to enhance the food safety. The future food safety measures demand better digital innovations to make the food supply chain safer and secured, with better traceability and accountability.

Data Ownership, Privacy, and Security: The growing digital trend in agri-food space in the form of cloud computing, IoT, and big data also comes with new challenges when it comes to cybersecurity. This is because, technologies like data platforms, wireless sensor networks, RFID, GPS, and business management systems can be vulnerable to breakdown, abuse, and misuse [126]. A breach of data security could be fatal to companies in terms of loss of business or reputation. While software companies constantly release updates to their applications and data platforms, updating is a very difficult task in some cases, for example, process control software. In addition, power failure is a common issue causing outages in farm-based IT systems.

While the use of data for AI approaches is seen as highly rewarding, there also exist many concerns, issues, and unaddressed questions around data ownership and privacy to be addressed. Since there is no guarantee that leakage of data upon sharing can be overruled, companies are hesitant to participate in AI efforts. Likewise, farmers, consumers, and smaller players in business are often left in dilemma with regards to their privacy or monetary share, should the data be used for commercial benefit. With regards to data ownership, blockchain being a peer-to-peer network that allows each participant to own his data and be involved in trade could prevent data monopoly. Efforts are needed to standardize the protocols used in the blockchain technology for its mass adoption, and its integration with AI for ensuring strong data immutability, greater transparency, and enhanced security. Smart contracts for data sharing and strong algorithms for data privacy are two important ways which can ensure that data's value is distributed without losing trust of the parties involved.

IX. Conclusion

IoT is recognized as one of the most important areas of future technology and is gaining considerable attention from a wide range of industries. With the implementation of IoT infrastructure in farming, farmers will be more efficient, intelligent, and connected, feeding vast amounts of information to analysts regarding crop yields, soil mapping, fertilizer applications, weather data, machinery, and animal health. The use of sensors is steadily increasing in early reporting of issues pertinent to crop health in farms, thereby enabling early checks for public health and safety. Efforts leading to easy integration of various IoT devices in terms of data and instruction flow from farm to consumer chain is important to obtain a viable and efficient IoT system.

The food supply chain industry is at the forefront of IoT adoption to track the consignments and reroute them in real time. Food quality and authenticity evaluation using miniature spectral cameras has become popular in the industry and efforts are underway to bring this capability to consumers through their smartphones. The industry is also exploring the benefits of the blockchain technology and next-generation genome sequencing for traceability in case of pathogen outbreaks and to ensure food safety. The huge volumes of data from social media is being analyzed for consumer behavior and crowdsourcing of ideas for new food product development.

In conclusion, the key performance indices that IoT and big data technologies will be potentially impacting are economical (e.g., increased productivity, lower production cost, and higher quality), environmental (e.g., less resource consumption, lower emission, and carbon footprint) as well as social (e.g., improved public health, consumer demand driven, and quality of life improvement). The pace of innovations in the field of IoT, big data, and AI are astounding and tasks that seemed impossible a few years ago have now been implemented with great success. Embracing the technology innovations and putting them to advantage are important for the success of modern agriculture and food industry.

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